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PATTERN RECOGNITION FOR STRUCTURAL HEALTH MONITORING

By

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ABSTRACT

The process of implementing a damage detection strategy for engineering systems is often referred to as *structural health monitoring*. Vibration-based damage detection is a tool that is receiving considerable attention from the research community for such monitoring. Recent research has recognized that the process of vibration-based structural health monitoring is fundamentally one of statistical pattern recognition and this paradigm is described in detail. This process is composed of four portions: (1) Operational evaluation; (2) Data acquisition and cleansing; (3) Feature selection and data compression, and (4) Statistical model development for feature discrimination. A general discussion of each portion of the process is presented.

1. INTRODUCTION

The process of implementing a damage detection strategy for aerospace, civil and mechanical engineering infrastructure is referred to as *structural health monitoring (SHM)*. Here *damage* is defined as changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the system's performance. The SHM process involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of system health. For long term SHM, the output of this process is periodically updated information regarding the ability of the structure to perform its intended function in light of the inevitable aging and degradation resulting from operational environments. After extreme events, such as earthquakes or blast loading, SHM is used for rapid condition screening and aims to provide, in near real time, reliable information regarding the integrity of the structure.

The basic premise of vibration-based damage detection is that damage will significantly alter the stiffness, mass or energy dissipation properties of a system, which, in turn, alter the measured dynamic response of that system. Although the basis for vibration-based damage detection appears intuitive, its actual application poses many significant technical challenges. The most fundamental challenge is the fact that damage is typically a local phenomenon and may not significantly influence the lower-frequency global response of structures that is normally measured during vibration tests. Another fundamental challenge is that in many situations vibration-based damage detection must be performed in an *unsupervised learning* mode. Here, the term *unsupervised learning* implies that data from damaged systems are not available. These challenges are supplemented by many practical issues associated with making accurate and repeatable vibration measurements at a limited number of locations on complex structures often operating in adverse environments. Recent research has begun to recognize that the vibration-based damage detection problem is fundamentally one of statistical pattern recognition and this paradigm is described in detail.

2. VIBRATION-BASED DAMAGE DETECTION AND STRUCTURAL HEALTH MONITORING

This statistical pattern recognition paradigm for structural health monitoring is composed of four portions: (1) Operational evaluation; (2) Data acquisition, cleansing and fusion; (3) Feature selection and data compression, and (4) Statistical model development for feature discrimination.

2.1 Operational Evaluation

Operational evaluation answers four questions in the implementation of a structural health monitoring system:

1. What are the economic or life-safety justifications for performing the monitoring?
2. How is damage defined for the system being investigated and, for multiple damage possibilities, which are of the most concern?
3. What are the conditions, both operational and environmental, under which the system to be monitored functions?
4. What are the limitations on acquiring data in the operational environment?

Operational evaluation begins to set the limitations on what will be monitored and how the monitoring will be accomplished. This evaluation starts to tailor the health monitoring process to features that are unique to the system being monitored and tries to take advantage of unique features of the postulated damage that is to be detected.

2.2 Data Acquisition and Cleansing

The data acquisition portion of the structural health monitoring process involves selecting the types of sensors to be used, selecting the location where the sensors should be placed, determining the number of sensors to be used, and defining the data acquisition /storage/transmittal hardware. This process is application specific. Economic considerations play a major role in these decisions. Another consideration is how often the data should be collected. In some cases it is adequate to collect data immediately before and at periodic intervals after a severe event. However, if fatigue crack growth is the failure mode of concern, it is necessary to collect data almost continuously at relatively short time intervals.

Because data can be measured under varying conditions, the ability to normalize the data becomes very important to the damage detection process. One of the most common procedures is to normalize the measured responses by the measured inputs. When environmental or operating condition variability is an issue, the need can arise to normalize the data in some temporal fashion to facilitate the comparison of data measured at similar times of an environmental or operational cycle. Figures 1 and 2 conceptually illustrate scenarios where measures of the environmental or operational parameter will and will not be need to be incorporated into the normalization procedure.

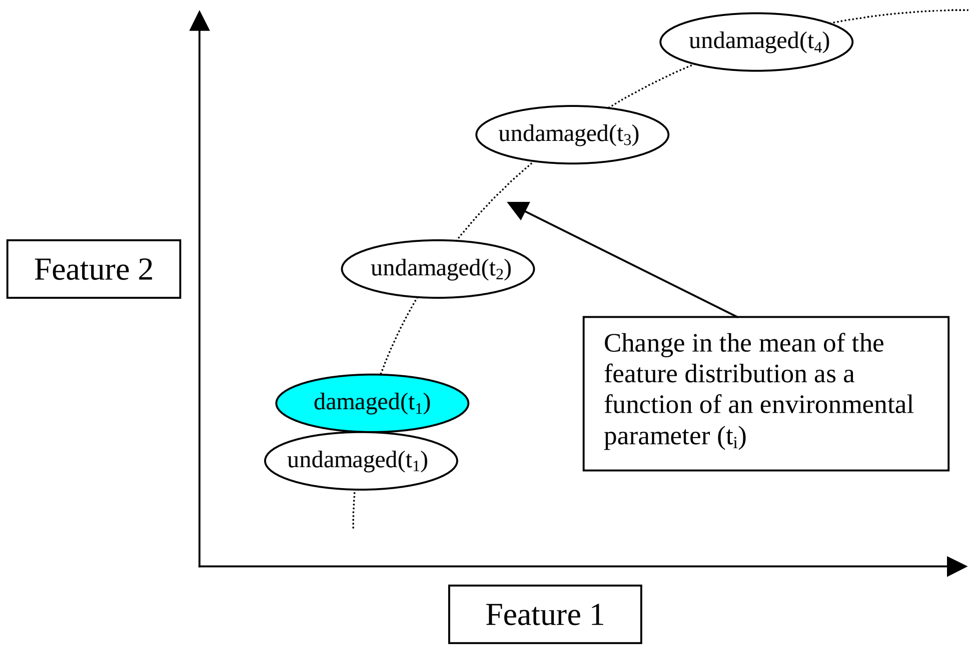

Figure 1 Damage produces changes in the feature distribution similar to those produced by environmental variability. This case will most likely require some measure of the environmental parameter to be included in the normalization process.

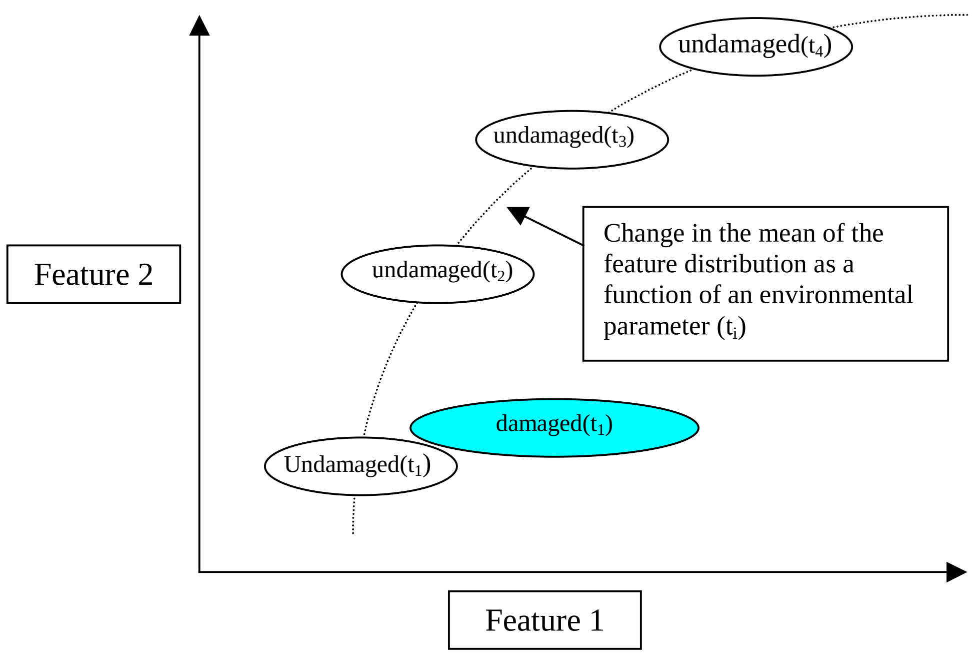

Figure 2. Damage produces a change in the feature distribution that is in some way orthogonal to changes caused by the environmental effects. For this case a measure of the environmental parameter may not be necessary.

Data cleansing is the process of selectively choosing data to accept for, or reject from, the feature selection process. The data cleansing process is usually based on knowledge gained by individuals directly involved with the data acquisition. Data fusion is concerned with integrating information from an array of heterogeneous sensors for better understanding of the system response. Finally, it is noted that the data acquisition, cleansing and fusion portion of a structural health-monitoring process should not be static. Insight gained from the feature selection process and the statistical model development process provides information regarding changes that can improve this process.

2.3 Feature Selection

The study of data features used to distinguish the damaged structures from undamaged ones receives considerable attention in the technical literature[1]. Inherent in the feature selection process is the condensation of the data. The operational implementation and diagnostic measurement technologies needed to perform structural health monitoring typically produce a large amount of data. Condensation of the data is advantageous and necessary, particularly if comparisons of many data sets over the lifetime of the structure are envisioned. Also, because data may be acquired from a structure over an extended period of time and in an operational environment, robust data reduction techniques must retain sensitivity of the chosen features to the structural changes of interest in the presence of environmental noise.

The best features for damage detection are typically application specific. Numerous features are often identified for a structure and assembled into a feature vector. In general, a low dimensional feature vector is desirable. It is also desirable to obtain many samples of the feature vectors for the statistical model building portion of the study. There are no restrictions on the types or combinations of data that are assembled into a feature vector.

2.4 Statistical Model Development

The portion of the structural health monitoring process that has received the least attention in the technical literature is the development of statistical models to enhance the damage detection. Almost none of the hundreds of studies summarized by Doebling, et al.[1] make use of any statistical methods to assess if the changes in the selected features used to identify damaged systems are statistically significant. However, there are many reported studies for rotating machinery damage detection applications where statistical models have been used to enhance the damage detection process[2].

Statistical model development is concerned with the implementation of the algorithms that operate on the extracted features to quantify the damage state of the structure. The algorithms used in statistical model development usually fall into three categories. When data are available from both the undamaged and damaged structure, the statistical pattern recognition algorithms fall into the general classification referred to as *supervised learning*. *Group classification* and *regression analysis* are general classes of algorithms for supervised learning. *Unsupervised learning* refers to algorithms that are applied to data not containing examples from the damaged

[1] Doebling, S. W., et al., (1998) "A Review of Damage Identification Methods that Examine Changes in Dynamic Properties," *Shock and Vibration Digest* **30** (2), pp. 91-105.
[2] Mitchell, J. S. (1992) *Introduction to Machinery Analysis and Monitoring*, PenWel Books, Tulsa.

structure. Some form of outlier detection is typically employed for the unsupervised learning problem.

The damage state of a system can be described as a five-step process along the lines of the process discussed in Rytter[3] to answers the following questions: (1) Is there damage in the system (existence)?; (2) Where is the damage in the system (location)?; (3) What kind of damage is present (type)?; (4) How severe is the damage (extent)?; and (5) How much useful life remains (prediction)? Answers to these questions in the order presented represents increasing knowledge of the damage state. The statistical models are used to answer these questions in a quantifiable manner. Experimental structural dynamics techniques can be used to address the first two questions. To identify the type of damage, data from structures with the specific types of damage must be available for correlation with the measured features. Analytical models are usually needed to answer the fourth and fifth questions unless examples of data are available from the system (or a similar system) when it exhibits varying damage levels.

Finally, an important part of the statistical model development process is the testing of these models on actual data to establish the sensitivity of the selected features to damage and to study the possibility of false indications of damage. False indications of damage fall into two categories: (1) False-positive damage indication (indication of damage when none is present), and (2) False-negative damage indications (no indication of damage when damage is present).

3. CONCLUDING COMMENTS

Current SHM methods are either visual or localized experimental methods such as acoustic or ultrasonic methods, magnetic field methods, radiograph, eddy-current methods and thermal field methods[4]. All of these experimental techniques require that the vicinity of the damage is known *a priori* and that the portion of the structure being inspected is readily accessible. The need for quantitative *global* damage detection methods that can be applied to complex structures has led to research into SHM methods that examine changes in the vibration characteristics of the structure. Summaries of this research can be found in recent review articles.[5,6] In addition, there are several annual and biannual conferences dedicated to this topic.[7,8,9] To date, most global SHM techniques proposed in these references examine changes in modal properties (resonant frequencies, mode shapes), or changes in quantities derived from modal properties. Drawbacks of these investigations include:

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[3] Rytter, A. (1993) “Vibration based inspection of civil engineering structures,” Ph. D. Thesis, Dept. of Bldg Tech. and Struct. Eng., Aalborg Univ., Denmark.

[4] Doherty, J. E. (1987) “Nondestructive Evaluation,” Chapter 12 in *Handbook on Experimental Mechanics*, A. S. Kobayashi Edt., Society for Experimental Mechanics, Inc.

[5] Doebling, S. W., C. R. Farrar, M B. Prime, and D W. Shevitz, (1996) "Damage Identification and Health Monitoring of Structural and Mechanical Systems From Changes in their Vibration Characteristics: A literature Review, Los Alamos National Laboratory report LA-13070-MS.

[6] Housner, G.W., et al., (1997) “Structural Control: Past, Present and Future,” (Section 7, Health Monitoring) *Journal of Engineering Mechanics*, ASCE, **123** (9), pp. 897-971.

[7] The 2nd International Structural Health Monitoring Workshop, Palo Alto, CA, 1999.

[8] The 5th International Symposium on Nondestructive Evaluation of Aging Infrastructure, Newport Beach, CA. 2000.

[9] The 3rd International Conference on Damage Assessment of Structures, Dublin, Ireland, 1999.

1. The use of relatively expensive off-the-shelf, wired instrumentation and data processing hardware not designed specifically for SHM.
2. Excitation has, in general, been from ambient sources inherent to the operating environment.
3. Ambient vibrations excite lower frequency global modes that are insensitive to local damage.
4. The data reduction is usually based on classical linear modal analysis.
5. Most studies assume that the structure can be modeled as a linear system before and after damage.
6. Statistical methods have not been used to quantify when changes in the dynamic response are significant and caused by damage. Varying environmental and operational conditions produce changes in the system's dynamic response that can be easily mistaken for damage.

Taken as a whole, the aforementioned characteristics place serious limitations on the practical use of existing methodologies. Indeed, with the exception of applications to rotating machinery, there are no examples of reliable strategies for SHM that are robust enough to be of practical use.

In an effort to address some of the deficiencies listed above a statistical pattern recognition paradigm for vibration-based structural health monitoring has been proposed. To date, all vibration based-damage detection methods that the authors have reviewed in the technical literature can be described by this paradigm with the vast majority of this literature focused on the identification of damage sensitive features. However, few of these studies apply statistical pattern recognition procedures to the damage-sensitive features. This lack of statistical analysis presents some potential problems for the development of vibration-based damage detection technology. As an example, the difficulties associated with accurately quantifying the statistical distribution of large order feature vectors are well documented in the statistics literature. However, most vibration-based damage detection methods discussed in the technical literature do not address this issue and many do not hesitate to suggest the use of relatively large feature vectors. A multi-disciplinary approach to the vibration-based damage detection problem is required to alleviate problems such as the "curse of dimensionality." Such approaches offer the potential to overcome other difficulties associated with this technology such as widely varying length scales of the damage relative to that of the structure and the fact that damage can accumulate vary gradually over multi-year time scales.